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An approach for mining concepts' relationships based on historical assessment records

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Abstract

In recent years, researchers have proposed various approaches for developing adaptive learning systems based on concept maps. Nevertheless, most of them deal only with binary grades of each test item. In this paper, we present a new method to automatically construct concept maps based on fuzzy set theory that can construct concept maps based on the result of analysis of numerical testing scores. The proposed method can overcome the drawbacks of existing methods and provides a useful way to automatically concept maps in adaptive learning systems.

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1. Introduction

In 1965, Zadeh proposed the concept of a fuzzy set to describe imprecision that is characteristic of much of human reasoning. Since that time, many adaptive learning and testing systems based on the fuzzy set theory and data mining have been proposed to find out the hidden relationships in the data collected during the learning process.

Historical testing records can be contain a huge mass of hidden data which can be useful for constructing concept maps of course, thus, applying the fuzzy set theory and data mining techniques are a powerful tool in discovering hidden knowledge from the testing results [1], therefore, many researchers

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have proposed various approaches and methods for developing adaptive learning systems based on concept maps.

In [2], Bai and Chen proposed a method for automatically constructing concept maps based on fuzzy rules. In [3], Lee et al. proposed a method to automatically construct concepts maps for conceptual diagnosis based on Apriori algorithm [4]. In [5], Chen and Sue proposed a method to automatically construct concepts maps based on four kinds of association rules. In [6], Chen and Bai proposed a method to automatically construct concept maps based on data mining techniques to overcome the drawbacks of Lee et al.'s method. In [7], Tsai et al. proposed a Two-Phase fuzzy mining to find the embedded association rules from the historical learning records of students. Nevertheless, most mentioned methods [2, 5, 7, 8, and 9] deal only with binary grades of each test item or do not take in consideration the conceptual weight of concept in each question that might be cause to construct incorrectly relationships or exaggerate the degree of relationship.

In real assessment environment, a short answer test also uses to assess the learning understanding, therefore, in this paper; we propose a new approach to automatically construct concept maps based on the result of analysis of numerical testing scores that can cope with the previously problem. First, we use look ahead fuzzy association rule mining algorithm to mind some information about the relationships between questions, then we construct the questions-relationships mapping [2]. After that, we calculate the relevance degree between concepts in each question to obtain the final concept maps.

2. A new approach for automatically mining the relationships between concepts

Let the test portfolio of the learners and the conceptual weight relationships into the matrix **G** and the matrix **QC**, where matrix **G** given as follows:

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix}_{n \times m}$$

, where "$g_{Si,Qj}$" denotes the score of question " " of the learner " ", "$g_{Si,Qj}$" [0,P], "P" is the maximum value that can obtain by learners, $1 \le i \le n$, $1 \le j \le m$, "n" is number of learners and "m" is number of questions.

The questions-concepts matrix shown as follows:

$$QC = \begin{bmatrix} qc_{11} & qc_{12} & \cdots & qc_{1p} \\ qc_{21} & qc_{22} & \cdots & qc_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ qc_{m1} & qc_{m2} & \cdots & qc_{mp} \end{bmatrix}_{p \times m}$$

, where "qc_{ij}" denotes the weighting or degree of relevance for each concept to each question integrated from multiple experts [11] and $0 \le qc_{ij} \le 1$.

If the membership functions of each quiz's grade are known and we fuzzificated the grade matrix to transform numeric grade to symbolic data, then we can apply the Look Ahead Fuzzy Association Rule Mining Algorithm (LFMAlg) [7, 10] to find the association rules of test item.

Let also based on the associated rules, we construct the two kinds of questions-relationship maps [6] as follows:

- For the association rule types "$Q_i, L \rightarrow Q_j.L$", "$Q_i, H \rightarrow Q_j.L$" and "$Q_i, H \rightarrow Q_j.H$" (the related explanations of the analysis are shown in Table 1), we build a relationship from question "Q_i" to question "Q_j".
- For the rules type " $Q_i, L \rightarrow Q_j.H$", we build a relationship from question "Q_j" to question "Q_i".

Assuming that, the confidence of an association rule be the confidence of the relationship between questions builds from it and for any two question, if the confidence of the questions-relationship between them is smaller than the minimum confidence "θ", then we delete the relationship between them to get the completed question-relationship map. If there is more than one relationship between any two questions, then we only keep the relationship with the maximum degree and delete the others.

Table1. The explanations of rule types [10]

Rule	Description of relationships
$Q_i.L \rightarrow Q_j.L$	It is means that the related concepts in question " Q_i" is the prerequisite of those in "Q_j" and explain why getting low grade in question "Q_i" might imply getting low grade on " Q_j"
$Q_i.L \rightarrow Q_j.H$	It is means that the related concepts in question "Q_j" is the prerequisite of those in "Q_i" because "Q_i" may be not learned well resulting from "Q_j"
$Q_i.H \rightarrow Q_j.L$	It is means that the concepts in question "Q_i" is the prerequisite of concepts in "Q_j"
$Q_i.H \rightarrow Q_j.H$	It is means that the concepts in question "Q_i" is the prerequisite of concepts in "Q_j"

For all kept association rules type " $Q_x \rightarrow$ " obtained in the previous Step, we calculate the relevant degree " $rev(C_i \rightarrow C_i)_{Q}$" between concepts " " and " " from the relationship " $Q_x \rightarrow$ ", as follows [3]:

$$rev(C_i \rightarrow C_i)_{Q_xQ_y} = W_{Q_xC_i} \times W_{Q_yC_i} \times conf(Q_x \rightarrow Q_Y). \tag{1}$$

Where " $rev(C_i \rightarrow C_i)_{Q}$" denotes the relevance degree of the relationship " $C_i \rightarrow$ " converted from the relationship " $Q_x \rightarrow$ ", $rev(C_i \rightarrow C_i)_{Q_xQ_y}$ [0,1], " " denotes a concept appearing in the question " ", " " denotes a concept appearing in the question " " ," W_C" denotes the weight of the concept " " in the question " " ," W_Q" denotes the weight of the concept " " in the question " ", " $conf(Q_x \rightarrow C$" denotes the confidence of the relationship " $Q_x \rightarrow$ " ,x ≠ y, 1≤ x ≤ m, 1≤ y ≤m and 1≤ i ≤p . Furthermore, let " $conf(Q_x \rightarrow C$" be the confidence of the relationship " $C_i \rightarrow$". If there is more than one relationship between any two constructed concepts, then the relationship between the two concepts chosen as follows:

$$rev(C_i \rightarrow C_j) = Max(rev(C_i \rightarrow C_j)_{Q_YQ_Y}). \tag{2}$$

As we got the initial concepts-relationships mapping, we must adjust those relationships, therefore, in the next step we create a new concept-concept matrix **C'** based on the conceptual weights found in matrix **QC**, shown as follows:

$$C' = \begin{array}{c|c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_n \end{array} & \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix} \end{array}, \quad b_{ij} = \begin{cases} 0, & i = j \\ \min(qc_i, qc_j), & i \neq j \end{cases}$$

, where "b_{ij}" denotes the minimum nonzero values in a concept C_i's column and C_j's column for all questions from matrix **QC**, $b_{ij} \in [0, 1]$ and $1 \leq i, j \leq n$.

Let $\mu = Min(b_{ij})$, where "μ" denotes the minimum nonzero value of the relevance degree in **C'** matrix and "μ" $\in [0, 1]$. For each relationship "$C_i \rightarrow C_j$", calculate the relative questions-concepts values between concepts "C_i" and "C_j" shown as follows:

$$Ret(C_i \rightarrow C_j) = N_i/N_j. \tag{3}$$

Where $Ret(C_i \rightarrow C_j)$ denotes the relative questions-concepts values between concepts "C_i" and "C_j", N_i denotes the number of the questions which have concept C_i and N_j denotes the number of the questions which have concept C_j.

$$Ret(C_i \rightarrow C_j) \times bij \geq \mu \;\&\; rev(C_i \rightarrow C_j) \geq \mu \tag{4}$$

If Eq. (4) true, add an edge from C_i to C_j into the concept map as with the relevance degree of relationship "$C_i \rightarrow C_j$" to construct a concept map. Otherwise, delete it. Finally, if there are more than one concept-relationships between concepts "C_i" and "C_j", then we only keep the concept-relationship with the maximum relevance degree and delete the others.

3. Conclusions

This study proposed an innovative approach to automatically construct concept maps. The proposed method is using the look ahead fuzzy association rules algorithm [7, 10], takes in consideration the conceptual weight of concept in each question and constructs concept maps based on the result of analysis of numerical testing scores. Firstly, we use look ahead fuzzy association rule mining algorithm to mind some information about the relationships between questions, then we construct the questions-relationships mapping [2]. After that, we calculate the relevance degree between concepts in each question to obtain the final concept maps.

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